# Methodology for Integrated Failure-Cause Diagnosis with Bayesian Approach: Application to Semiconductor Manufacturing Equipment

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## ABSTRACT

Semiconductor Industry (SI) is facing the challenge of short product life cycles due to increasing diversity in customer demands. As a result, it has transformed into a high-mix low -volume production line that requires sustainable production capacities. However, significant increase in the unscheduled equipment breakdowns, limits its success. It is observed that in a high-mix low-volume production, product commonality is inversely proportional to failure occurrences and number of corrective actions in each failure. This provides evidence of misdiagnosis for equipment failures and causes. Moreover, equipment is believed to be the only source for product quality drifts that increase the unscheduled breakdowns and result in unstable production capacities. In this paper, we propose two defense lines against increasing unscheduled equipment breakdowns due to misdiagnosis. We argue that product quality drift can be traced to product itself, process and maintenance events, besides equipment. The Bayesian Belief Network (BBN) is proposed using symptoms, collected across drift sources, that improves equipment breakdown decisions by accurately identifying the source of product quality drift. The misdiagnosis of equipment failures and causes, if equipment is found as a source of drift, is another significant factor for increasing unscheduled equipment breakdowns. Existing failures and causes diagnosis approaches, in the SI, model equipment as a single unit and use fault detection and classification (FDC) sensor data. We also argue that these are the key reasons for the misdiagnosis because of neglected facts that production equipment is composed of multiple modules and FDC sensors undergo reliability issues in a high-mix low-volume production line. Therefore, to improve these misdiagnosis, another BBN is proposed that uses statistical information, collected from the equipment database, at the module level. These BBN models are evaluated in a thermal treatment (TT) workshop at the world reputed semiconductor manufacturer. The BBN model for the identification of the source of product quality drift (failure mode) demonstrates 97.8% prediction accuracy; whereas, module level BBNs for equipment failures and causes diagnosis are found 45.7% more accurate than equipment level BBN.



## 1. INTRODUCTION

The SI has revolutionized our daily lives with integrated circuit (IC) chips and on the average we use more than 250 chips and 1 billion transistors per day per person. These chips are installed in almost all the equipment around us ranging from dish washer, microwave ovens and flat screens to office equipment. The sales revenues in the SI are characterized with cyclic demand patterns and positive compound annual growth rate (CAGR) of 8.78% (Figure 1). This ensures that demand driven downfalls will follow a cumulative growth. It also motivates the SI to continuously introduce new technologies and improve their existing processes to address the challenge of high-mix low-volume production and capture maximum market share.

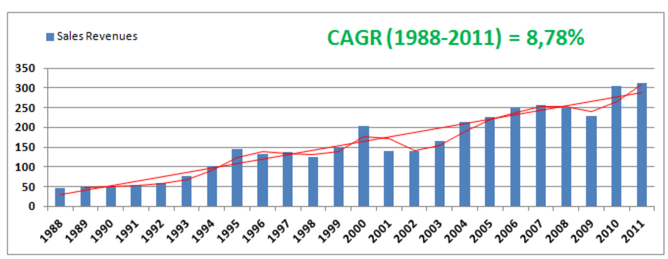
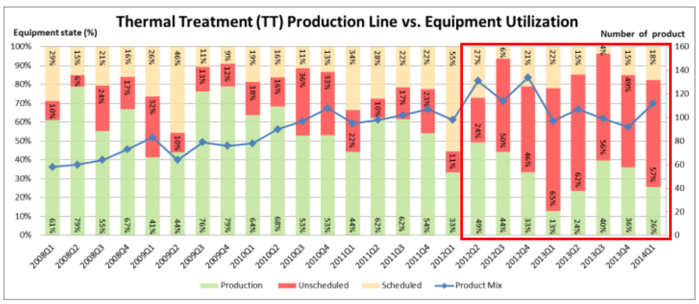



Figure 1 - Global sales revenues of SI[1]

[1] The data is collected from the well known technology research centers (i) Gartner {www.gartner.com} and (ii) isuppli {www.isuppli.com}

The demand for integrated circuits (ICs) is mainly driven by end-user markets from electronics industry (EI) e.g. data processing, automotive industry, consumer electronics, communications and industrial sector (Ballhaus, Pagella, & Vogel, 2009). The SI forms a part of this complex interaction among these multiple industrial sectors (Yoon & Malerba, 2010; Kumar, 2008). Wireless communication and consumer electronics are leading market segments whereas automotive is a potential emerging segment. At present, the automotive market is only 8% of the total SI market but is expected to dominate in near future. Demand is continuously increasing not only in volume but also in diversity. This diversity has witnessed significant growth that ultimately leads to short product life cycles (Shahzad, Hubac, Siadat, & Tollenaere, 2011).

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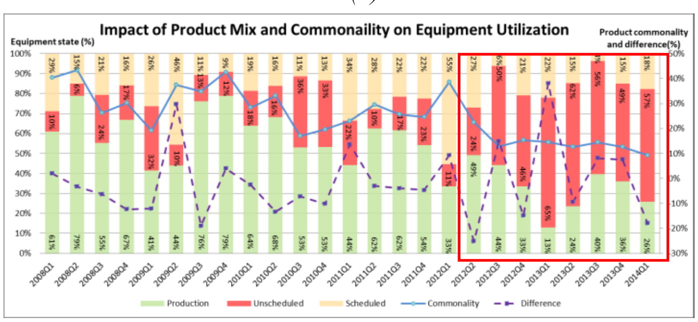
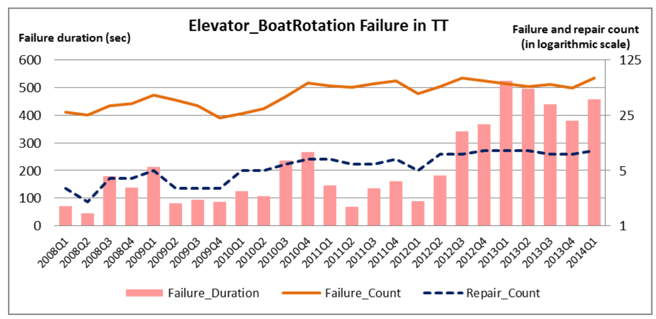



*(b)*

Figure 2 - Product mix , commonality and differentiation vs. equipment utilization[2]

The Figure 2 above presents equipment utilization for a thermal treatment (TT) workshop at the world reputed semiconductor manufacturer. This data is aggregated at the quarter level and spans over last six years (2008Q1 to 2014 Q1). It is also manipulated for the confidentiality purposes; however, scale is kept constant to keep the original trends. It can be seen that during 2008Q1 and 2012Q2, production capacities are significantly larger than both scheduled and unscheduled breakdowns (Figure 2a). In this period, we can observe a slight increase in the product mix that decreases production capacities. The data till 2014Q1 shows that with the fluctuation of the product-mix, the production capacities suffers unstability and a notable decline. The Figure 2b presents the impact of product differentiation and commonality for two consecutive quarters on the equipment utilization. The difference in product mix is plotted on secondary y-axis. This can be positive or negative and ranges from -25% to +38%; whereas, product commonality is plotted on the primary y-axis for each current quarter, that ranges from 49% to 92%. It can be observed that production capacities increase with an increase in product commonality and are inversely related to unscheduled breakdowns. Therefore, the production learning curves against demand diversity can be improved by reducing not only unscheduled breakdowns but also by stabilizing them. In last two years, high product mix and short product life cycles that result in product differentiation has reduced TT workshop production capacities to 30%. It is because of unscheduled equipment breakdowns that result in the waste of resources and global productivity due to interruption in the time constraint production schedules. However, corrective maintenance due to these breakdowns is unavoidable.

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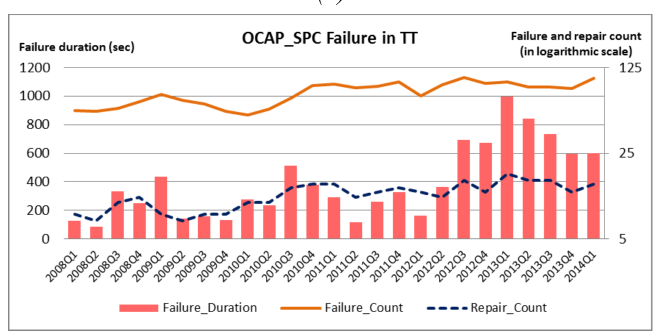


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Figure 3 - Failure counts, durations and occurrences

Further analysis on the failure durations (primary y-axis), occurrences, and number of repair actions (secondary y-axis) in each failure are plotted and presented in Figure 3, using data collected from TT equipment. The data is plotted for two significant failures: (a) elevator boat rotation and (b) OCAP_SPC and it is manipulated due to confidentiality. It can be seen that failure count and average number of repair actions in each failure occurrence are inversely proportional to product commonality. However, OCAP (out of control action plan) failure occurrence is relatively higher (30%)

[2] The production line data from thermal treatment (TT) production line is manipulated with a constant for confidentiality while not losing the insight in reduced production capacities.

than elevator boat rotation. The increase in number of repair actions in a failure occurrence provides significant evidence for misdiagnosis that is one of the key factor for increasing unscheduled equipment breakdowns in a high-mix low-volume production lines e.g. SI.

In addition to equipment failures and causes misdiagnosis, we also argue that misdiagnosis can occur while identifying the source of product quality drifts. In a highly complex production environment as SI, we believe that the source of such drifts can be equally traced to other elements such as products, process, equipment and maintenance; however, at present it is believed to be the equipment. This paper is divided in 4 sections. Section-2 presents related literature review on equipment failure-cause diagnosis in general and specially in the SI, and the evidence that equipment is taken as the only source of product quality drift. The proposed methodology and the case study are presented in section-3 whereas BBN models and analyses results are presented in section-4. Finally, we conclude this paper with discussion and perspectives.

## 2. LITERATURE REVIEW

For clear orientation, we refer to the SEMI standard definition[3] of failure as an unplanned event that changes an equipment (system) to a condition where it cannot perform its intended function. Whereas, cause or fault is the reason behind the occurrence of failure in the equipment. It is different than the source of product quality drift, referred as failure mode (FM), in this paper. The FM is the category of cause behind a product quality drift. For example, due to the type of TT equipment (batch cluster) where multiple lots are processed together; a drift might occur due to the influence of different product combinations. In such situation, the FM is the product and not equipment; therefore, equipment must not be stopped for the failures and causes diagnosis, and associated corrective maintenance actions. In this regard, section 2.1 presents analysis on the product quality drift sources. The section 2.2 presents the existing equipment failure-cause diagnosis in the SI and section 2.3 presents the choice of BBN as our target approach for modeling the FM identification and equipment failures and causes diagnosis.

### 2.1. Source of Product Quality Drift Analysis

Analysis of the source of product quality drift can be related to Root Cause Analysis, a study to diagnose the sources of problems in processes for directing counteractive actions (Rooney & Heuvel, 2004). Doty (1996) and Smith (2004) used the classification by Ishikawa and Loftus (1990) to divide the root causes into six assignable categories of Man, Machine, Method, Material, Measure and Environment to explain abnormal situations in statistical process control strategies. It is a qualitative method, used frequently in the diagnosis domain, but requires long brainstorming sessions with experts and is performed on the occurrence of each new excursion. Therefore, it cannot be used in the complex production environment. Weidl, Madsen, and Israelson (2005) model industrial process and product failure control system using generic object oriented Bayesian Network that proposes corrective maintenance actions with explanation of root causes. Their set of root causes contains all possible hypotheses on failure sources or conditions coming from equipment sensors and process operations. Sarkar (2004); Demirli and Vijayakumar (2010) have combined cluster analysis with engineering knowledge to classify big set of equipment failure events into small number of categories and use the knowledge to identify root causes for each cluster.

These above researches are important as they provide the possibility of finding the true source of product quality drift. However, the problem for process and product is always associated to an equipment and then further investigation is made to find other probable causes. As a matter of fact, in the SI, a product quality drift is associated to a failure in the equipment; whereas, in reality, it can be traced to other assignable causes as demonstrated by Ishikawa diagram. We suggest to combine the advantages of the qualitative method (Ishikawa diagram) with probabilistic approach (BBN) to improve decisions on equipment stoppage against product quality drifts. This will act as a first line of defense to accurately identify the source of product quality drift and reduce unscheduled equipment breakdowns. The details can be found in sections 3.1 and 4.1.

### 2.2. Equipment Failure and Cause Diagnosis in the SI

Recent IT revolutions have enabled huge data volumes with improved artificial intelligence (AI) techniques for failure diagnosis. The commonly used techniques to optimize the production operations are advanced process control (APC) methods that include run to run (R2R) loops, statistical process control (SPC) and fault detection and classification (FDC). Chen and Blue (2009) have proposed an approach using EWMA (exponentially weighted moving average) chart as a function of variance and covariance of relevant parametric distributions to classify the bad equipment. It is comparable to FDC approach that uses SPC to model temporal patterns and to monitor and detect shifts or drifts in the equipment signals (Yue & Tomoyasu, 2004; Lacaille & Zagrebnov, 2007; He & Wang, 2007). This approach is objectively different than the above approaches as it integrates all sensors to generate one single index that reflects the overall equipment health against product quality. (Chang, Song, Kim, & Choi, 2012) proposed a fault detection and classification methodology for the SI using a sequential SVDD (support vector data description) classifier

[3]SEMI International Standards: Compilation of terms (Updated April 2014), retrieved on 4th June 2014 from: http://www.semi.org/en/sites/semi.org/files/docs/CompilationTerms0414.pdf

algorithm. It is a probabilistic modeling used in addition to statistical approach

A careful analysis of the existing approaches, methods and techniques, highlights that till today, to model a failure and cause diagnosis, sensors data are used. In addition, above discussion also highlights that the diagnosis models model equipment as a single unit for failures and causes diagnosis; whereas, an equipment is composed of multiple modules.

### 2.3. Bayesian Belief Network (BBN) as Modeling Tool

The methods used for failure and cause diagnosis range from univariate and multivariate statistical to artificial intelligence (AI) and machine learning (ML) methods. There do exist hybrid methods; however, most promising and suitable technique found in literature is the BBN. The advantage of using Bayesian network is its inherent ability for deduction and inter-causal reasoning (Kjærulff & Madsen, 2006). The deductive (causal) reasoning takes into account the causal links between variables, from causes to effects using dynamic detection evolution. The inter-causal reasoning is interesting and powerful ability of BBN where evidence on one possible cause disapproves other possible causes. In addition to their ability to represent causal relationships, BBN has the capacity to perform data learning efficiently in uncertain environments, involving small amount of data and short temporal change of states. It can be used to represent compact joint probability distributions (Margaritis, 2003).

The Bayesian network based approach has recently become focus for dynamic maintenance management and failure diagnosis in the SI. Yang and Lee (2012); Bouaziz, Zamaï, and Duvivier (2013) applied BBN for diagnostics and prognostics in the semiconductor manufacturing with an objective to investigate the causal relation among equipment conditions and their affects on product quality. Moreover, there do exist published methods and algorithms to adapt the BBN to fit to specific case studies in the SI (Roeder, Schellenberger, Schoepka, Pfeffer, Winzer, Jank, & Pfitzer, 2011). In the process industry, Isham (2013) proposed a BBN to compute dynamic probabilities and update the Fault Semantic Network. Its focus is on predicting real time risk based accident forecasting in oil and gas sector. Another important use of BBN is as a classifier and isolater of faults (Verron, Li, & Tiplica, 2010). Weber and Jouffe (2006) present a detailed review of BBN application in the domains of reliability, risk analysis and maintenance.

A traditional BBN consists of a set of nodes representing random variables (V), set of arcs (A) connecting these nodes to form a directed acyclic graph (DAG) (equation 1) and conditional probability distributions (CPD) tables to quantify the probabilistic relationships between nodes. The BBN is a graphical representation of joint probability distribution (equation 2) that represent dependent and conditionally independent relationships.

$$\text{Directed Acyclic Graph,} \quad G = (V, A) \tag{1}$$

$$P(X_1 = x_1, \ldots, X_n = x_n) = \prod_{i=1}^{n} P(X_i = x_i \mid \text{Parents}(X_i)) \tag{2}$$

This probabilistic representation of a system in a graphical form allows monitoring relationships among different variables. The CPD table is constructed based on the Bayes rule (equation 3) which states that for given 2 events A and B, the probability of A given B is the function of conditional dependence of B to A and respective probabilities of having A and B events together. It is an efficient feature to model causal relationships between a set of event.

$$P(A \mid B) = \frac{P(B \mid A)P(A)}{P(B)} \tag{3}$$

The distribution changes when the states of the nodes in G experience a change of events (called evidence). Propagation algorithm is used to fuse and propagate the impact of new evidence and beliefs through BBN so that each proposition eventually will be assigned a certainty measure, consistent with the axioms of probability theory (Pearl, 1988).

It is a powerful method for probabilistic knowledge representation and inference under uncertainty. The maintenance personnels make decisions to stop the production equipment, in case of product quality drift, under uncertainty. Therefore, BBN is the approach that offers probabilistic contextual information to make accurate decisions. It must be noted that every bad decision adds to unscheduled equipment breakdowns.

In this paper we focus on presenting a methodology to :

- *I*dentify the failure modes (source of product quality drift) as either product, process, equipment or maintenance. Therefore, we first develop a BBN that identifies the failure modes (section 4.1), accurately.
- *D*evelop integrated failure-cause diagnosis BBN models at the module and equipment level (sections 4.2 and 4.3). The existing equipment level BBNs are based on FDC sensors data that is no more reliable due to high-mix low-volume production.
- *U*se product, process, maintenance and equipment data/information. The key advantage of this data is that it is not subjected to reliability issues like FDC sensors (Blue, Roussy, Thieullen, & Pinaton, 2012).

## 3. PROPOSED METHODOLOGY

In this section, we elaborate the proposed methodology used to achieve the previously discussed objectives, followed by the description of case study, data processing and a brief presentation of BBN learning strategies.

### 3.1. Proposed BBN Based Methodology

In step-1, we start with the classification of potential symptoms from product, process, equipment and maintenance databases. The FDC sensor signals within equipment database are not directly used as symptoms; however, decisional data/information based on these signals is used as potential symptoms, failures and causes. It is due to the fact that emerging sensor reliability issues are linked with high-mix low-volume production and could result in unstable models. The FM are modeled as a function of symptoms and resulting BBN for FM identification serves as first defense against unscheduled equipment breakdowns. It help equipment engineers to make accurate decisions on stopping the equipment if the product quality drift is not related to product, process or maintenance. The step-2 in this methodology advocates to model equipment failures and causes as a function of symptoms using module level BBNs. We also model the equipment level BBN in step-3 to assess the assumption that module level BBNs are more accurate in failure-cause diagnosis than the equipment level model. The equipment level BBN is modeled and proposed to be updated upon new excursions where any structural change between two consecutive equipment level BBNs will be used as the signal to revise the module level BBNs, with expert's intervention. This loopback step is not completed in this case study; however, diagnosis results from module and equipment level models are compared based on their accuracies as the final step of this methodology.

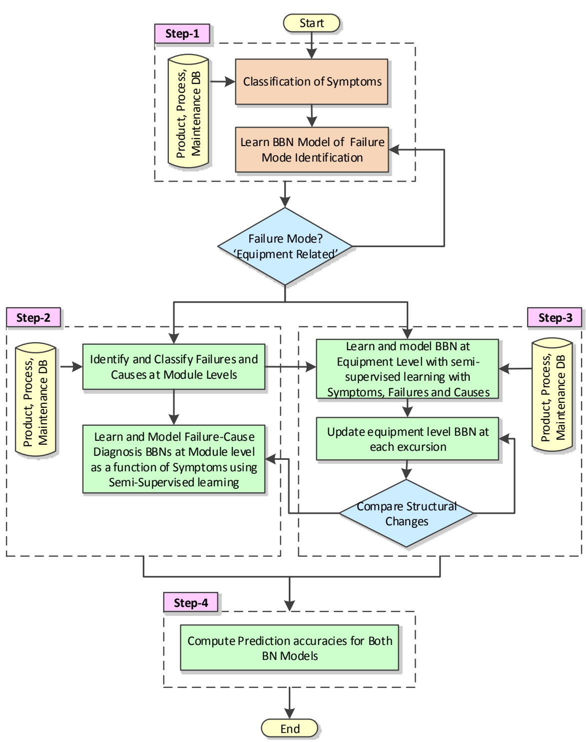
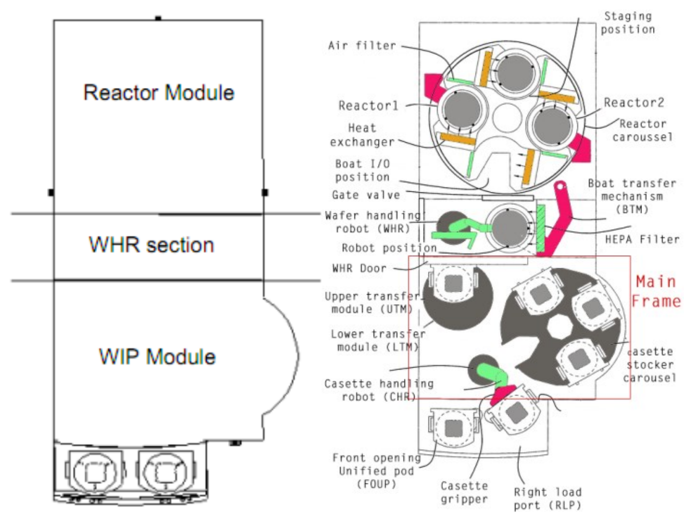



Figure 4 - Proposed 4-step methodology for integrated failures-causes diagnosis

### 3.2. Description of the Case Study for Thermal Treatment (TT) Workshop

As a case study, we consider TT workshop equipment, used to grow oxide and deposit nitride layers on the surface of silicon wafer as dielectric, respectively. This equipment uses low pressure chemical vapor deposition (LPCVD) as the technique to deposit nitride layers. It is also used for annealing (heat treatment) after production steps to stabilize the crystalline structure of a silicon wafer, prior to the next steps. The equipment type in this production line is batch cluster with two process chambers known as reactors (Figure 5). The structure of the TT equipment is presented in Figures 5a and 5b, below. The reactor, wafer handling robot (WHR) and work in progress (WIP) are the three main modules. Each of these modules is further composed of many sub modules (Figure 5b). In this case study, we consider three modules Reactor1, Reactor2 and Mainframe for demonstration with an assumption that these constitute the whole equipment. The integrated failure-cause diagnosis BBN models at module and equipment levels are therefore developed for these equipment modules.




(a) (b)

Figure 5 - View of the vertical LPCVD (Selen, Timmermans & Bolscher, 2009)

### 3.3. Data Processing

The dataset used in this case study spans six months (from week $27^{th}$ to week $52^{nd}$ of 2013) and are collected across product, process, equipment and maintenance databases for TT equipment. These are used in symptoms, failures and causes identification. The symptoms are classified into four categories and are used to generate the BBN to accurately identify the FM as the function of symptoms (section 4.1) as well as the development of an integrated failure-cause diagnosis BBN models at the module and equipment level (sections 4.2 and 4.3).

### 3.4. Bayesian Belief Network Learning

The BBN networks can be obtained either through experts knowledge or based on data learning. In the proposed methodology, the latter option is used. The BBN models are learned with BayesiaLab 5.3 using equivalence class (EQ), Taboo and Taboo order algorithms that use minimum description length (MDL) as an objective function. The brief summary of BBN learning with these methods is presented in Table 1. The models are learned first using EQ followed by optimization with Taboo and Taboo order. The model with lowest MDL score is accepted for further analysis. All BBN models are learned and tested using 75-25 cross validation strategy. The evaluation of BBN networks performance is presented in section 4.

| Function | Algorithm | | Strength | | References | |
|---|---|---|---|---|---|---|
| BBN structure building | Equivalence Class (EQ) | | Reduce search space efficiently | | (Chickering, 2002; Munteanu & Bendou, 2001) | |
| BBN structure optimization | Taboo | Taboo Order | Capacity to refine a developed model | Ability for exhaustive search with accurate results (given additional time) | (Glover, 1986) | (Teyssier & Koller, 2005) |
| BBN structure choice (function objective) | Minimum Description Length (MDL)<br>Target : Lowest MDL score | | Tradeoff between accuracy and complexity : application to multiply connected belief network | | (Lam & Bacchus, 1994) | |

Table 1 - Learning Bayesian network structure with BayesiaLab

## 4. MODELLING AND ANALYSIS RESULTS

In this section, we present the modeling and analysis results of BBN models as proposed in the methodology (section 3.1).

### 4.1. Classification of Symptoms and FM Identification (Step-1)

The identification and classification of potential symptoms from the database is the most difficult and complex task. It is because one needs to have multidisciplinary expertise from product, process, equipment and maintenance domains. This difficulty was addressed by a task force with experts from each discipline. The brainstorming sessions resulted in the formalization of well known Ishikawa (a.k.a. Fishbone) diagram (Ishikawa & Loftus, 1990) to find potential symptoms across product, process, equipment and maintenance areas. The results are presented in Figure 6.

Symptoms are classified in four axes as product, process, equipment and maintenance. The TT equipment is of batch cluster type; hence, they process multiple lots in a given step. Therefore current/previous product combinations might influence the product quality. Number of reworks, wait time before process and defect distribution from previous steps are also identified as key product symptoms linked with product quality drift. The process capability (Cp) and process capability index (Cpk) are the key process symptoms. It is also identified that not only current recipe but also previous recipe and their respective process steps combinations could be strongly linked with product quality. The FDC sensor signals from equipment database are not directly considered; however, decisional information based on these signals is a good candidate for potential symptoms. The key symptoms are equipment capability (Cm) and equipment capability index (Cmk); however, overall equipment efficiency (OEE) indicators and counters are the additional symptoms included . The counters are the meters associated with equipment modules (process chambers and mainframe), used for triggering preventive maintenance. The last category of symptoms is the maintenance where reliability, availability and maintenance (RAM), and failure indicators are identified as the key symptoms. The data is collected for these symptoms against product quality drifts. The data for OEE, RAM, process and equipment capability, and failure indicators are aggregated on weekly basis whereas rest of the data is instantaneous for a given product and process step.

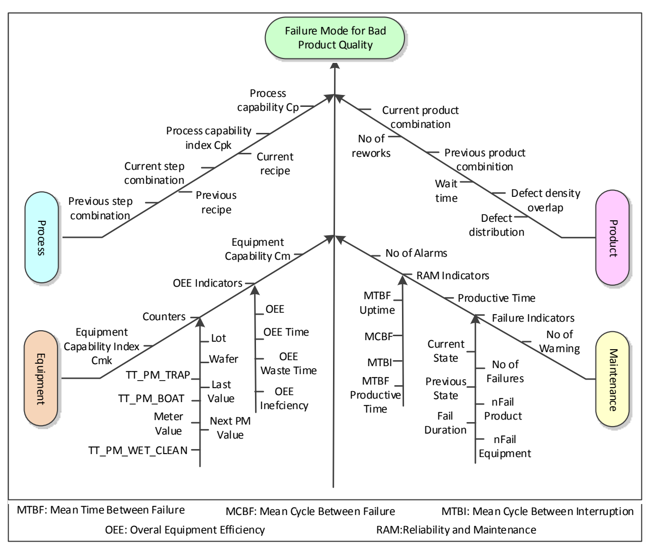



Figure 6 - Classification of symptoms

The BBN to identify potential failure modes (equipment, product, process and maintenance) is learned with BayesiaLab, using symptoms as recognized in Figure 6. The model is presented in Figure 7 where FMs are modeled as the function of symptoms. In this paper, the concept of prediction is used to represent inference results of a target node.

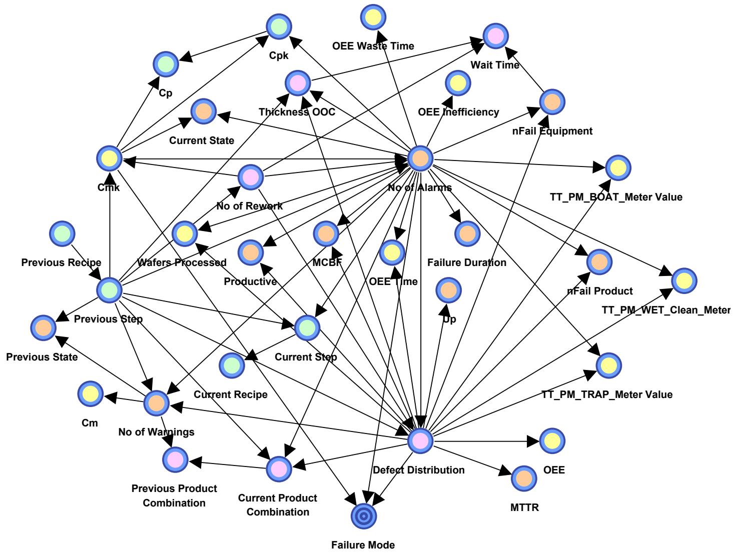



Figure 7 - BBN model for FM identification

The symptoms in this model are grouped into four categories as differentiated with different colors. The green, pink, yellow and light brown represent process, product, equipment and maintenance related symptoms, respectively. The target node is the failure mode. The objective of showing this graph (Figure 7) is to present the complexity of resulting network. The proof of concept and few results are presented in Figures 8 and 9. It can be seen that, BBN identifies product (64%) or maintenance related (36%) for a given set of symptoms as shown in the Figure 8. Hence, in this situation, maintenance personals should not stop the equipment.

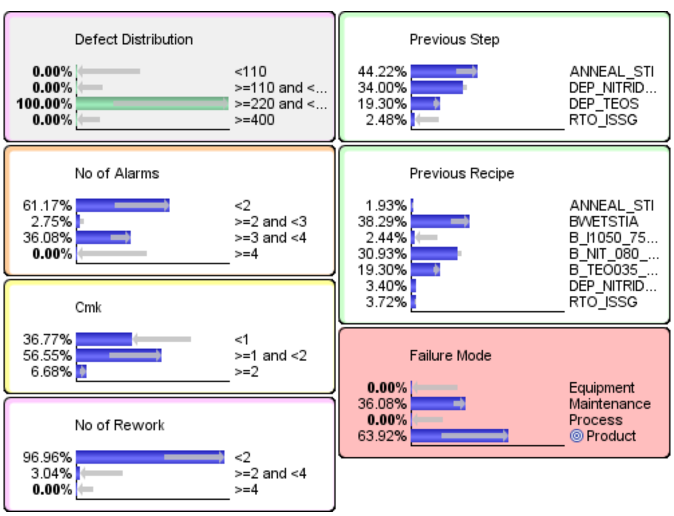



Figure 8 - Proof of concept: product as the FM

Similarly, the Figure 9 shows that maintenance is found as the only reason against given symptoms; hence, BBN model suggests to stop the equipment for further investigation on failures and causes. The precision and reliability matrices of the BBN model to identify the FM are presented in Figure 10. It can be seen that this model offers 97.8% precision on 75-25 cross validation strategy. In this strategy, 75% data is used to learn the model whereas 25% data (randomly selected) is used for precision and reliability measures.

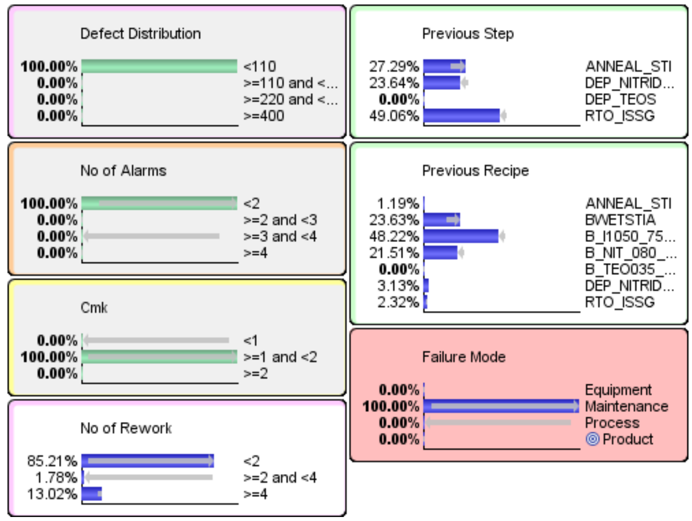
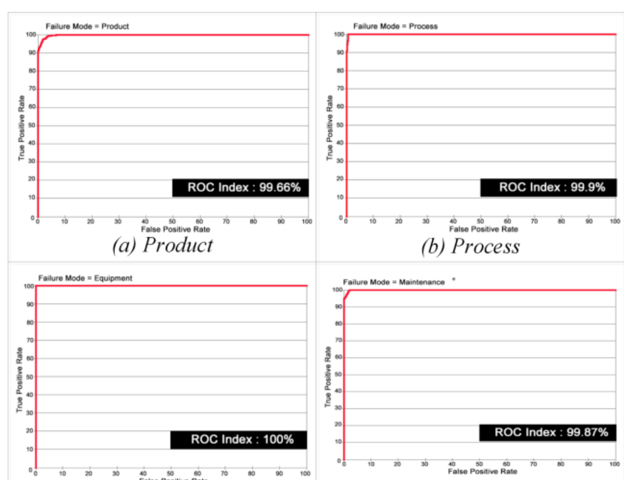



Figure 9 - Proof of concept: maintenance as the FM

| Value (Precision) | Equipment (1533) | Maintenance (1417) | Process (1015) | Product (1035) |
|---|---|---|---|---|
| Equipment (1533) | 100% | 0% | 0% | 0% |
| Maintenance (1338) | 0% | 94.42% | 0% | 0% |
| Process (1043) | 0% | 0% | 100% | 2.71% |
| Product (1086) | 0% | 5.58% | 0% | 97.29% |

| Value (Reliability) | Equipment (1533) | Maintenanc (1417) | Process (1015) | Product (1035) |
|---|---|---|---|---|
| Equipment (1533) | 100% | 0% | 0% | 0% |
| Maintenance (1338) | 0% | 100% | 0% | 0% |
| Process (1043) | 0% | 0% | 97.32% | 2.68% |
| Product (1086) | 0% | 7.27% | 0% | 92.73% |

Figure 10 - Precision and reliability of FM BBN




(a) Product (b) Process

(c) Equipment (d) Maintenance

Figure 11 - Prediction accuracy with ROC curves

Figure 11 shows FM prediction accuracy evaluation using receiver operating caracteristic (ROC) curves, a graph to plot true positive rate (Y-axis) against false positive rate (X-axis). Its index represents the surface under the ROC curve divided by the total surface and in this graph it represents an 99.88% average accuracy with 0.02% of false positive prediction. The capability of FM identification model with gain curves is presented in Figure 12. The yellow line (Figure 12c) presents that 31% of the test cases have 'equipment' as FM whereas the red curve represents the capability to predict them correctly in comparison with random prediction represented by the blue curve. The x-axis represents rate of individual cases taken into account for prediction whereas y-axis represents rate at which they are predicted accurately with target failure mode. The Gini index represents the gain over random model and is computed by dividing the area below red curve and above blue curve with the area under blue curve. The FM identification capability for product and process are higher than the equipment and maintenance. The relative Gini index is computed by dividing the area within triangle formed due to crossing of red, blue and yellow lines with area under blue curve.

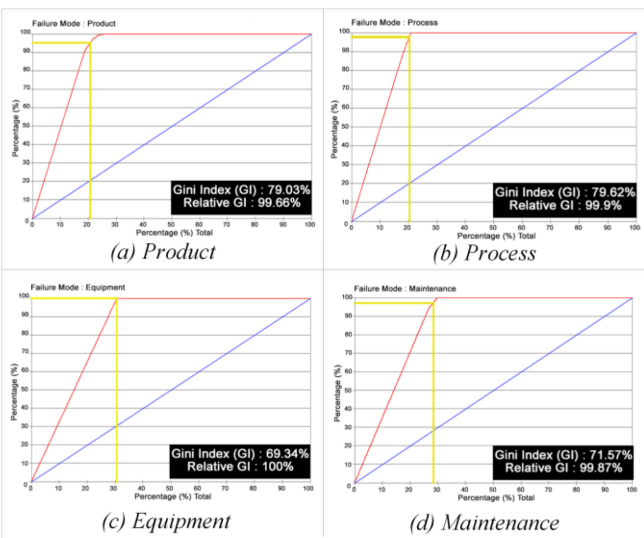



Figure 12 - FM identification model capability with gain curves

## 4.2. Module Level Failures-Causes Diagnosis BBN Models (Step-2)

The FM identification model, presented in previous section, is the first step towards reducing unscheduled equipment failure breakdowns. This is complemented by failures and causes diagnosis through BBN model, developed at module level where data on failure and causes are collected from the world reputed semiconductor manufacturer for the LPCVD process equipment (sections 3.2 and 3.3). For demonstration, we have used three modules (i) Reactor1, (ii) Reactor2 and (iii) Mainframe. The reactors are the process chambers where multiple lots are processed together for annealing, oxidation or metrication depositions (section 3.2). The Mainframe module is also referred as WIP module (see Figure 5) .

The BBN model for Reactor1 is presented below in the Figure 13 whereas BBN models for other modules are not presented due to space restrictions. The target nodes Failure Code1 and Failure Code2 are modeled as the function of symptoms; however, causes are also allowed to be directed from these symptoms. The color scheme for symptom classes is same as presented in section 4.1 whereas causes and failure codes are added with new colors (orange and blue respectively). The nodes not connected in these models are found with zero influence on either failure codes or causes.

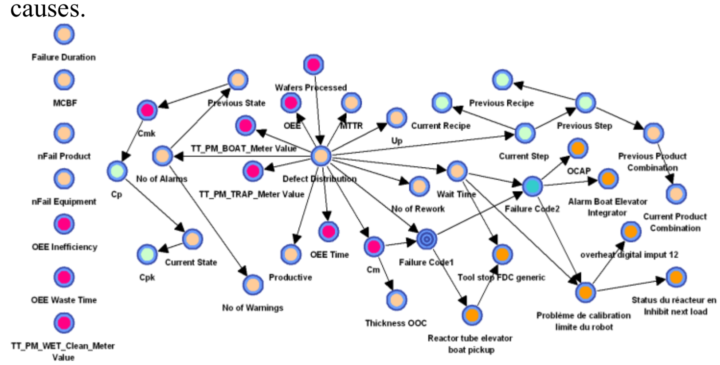



Figure 13 - Failure-Cause BBN diagnosis models for Reactor1

The example as proof of concept from the learned models is shown below in the Figure 14 for Reactor1. The equipment failures-causes diagnosis made by BBN model is presented as the function of symptoms in green rectangle.

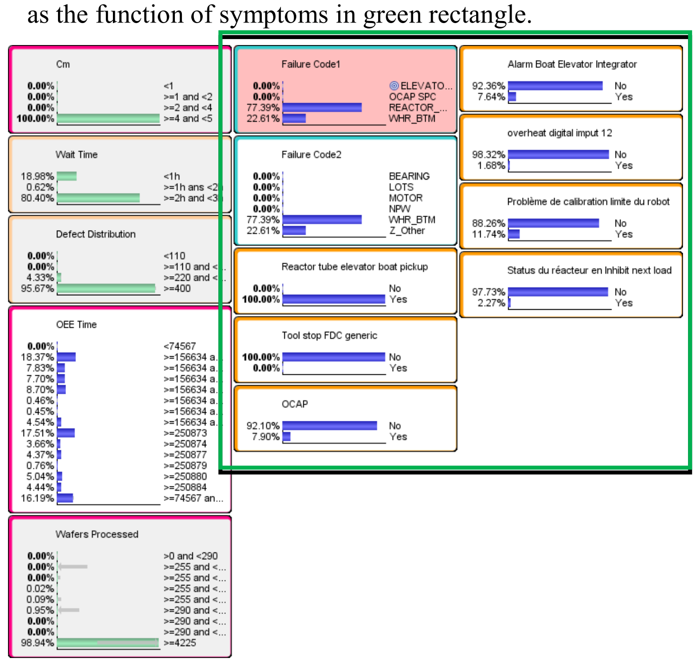



Figure 14 - Result from module level Reactor1 model

The prediction capability for learned models are presented below in Figure 15. The results show that learned models have high precision and accuracy. Besides this, it can also be observed that accurate prediction capabilities are also very high in terms of Gini indices.

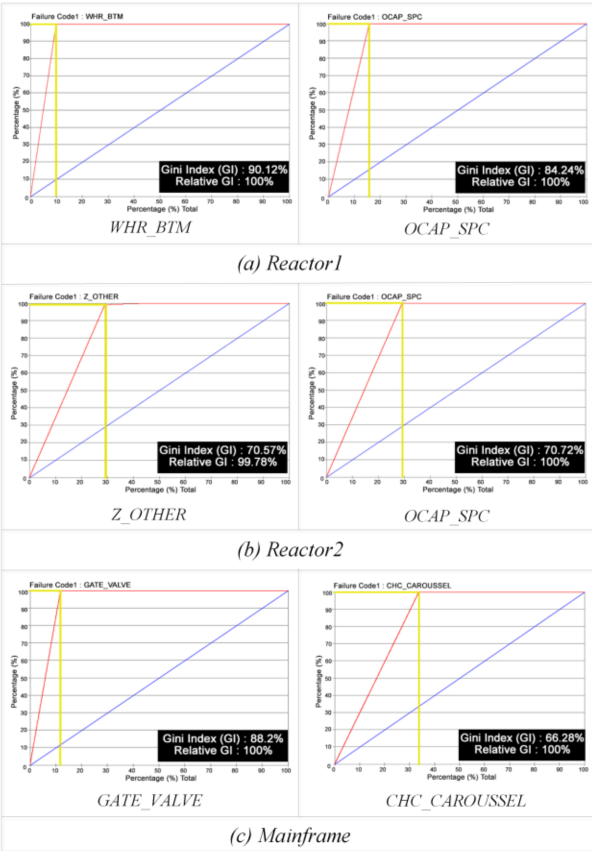



Figure 15 - Gain curves for BBN models

### 4.3. Equipment Level Failures-Causes Diagnosis BBN (Step-3)

To find out, whether module level BBN models are more accurate than equipment level BBN model, we developed an equipment level diagnosis model to find failure and causes. The symptoms from FM identification model (section 4.1) plus failures and causes from module level BBNs (section 4.2) are used to develop equipment level BBN model. Besides this, we add one node 'Module' to diagnose failure for a given module in the equipment. The model is presented below in the Figure 16. It can be seen that all nodes are connected. The nodes that have zero influence in module level BBNs, appear connected in this network that add confusion and influence the equipment level failures-causes diagnosis. Confusion is also caused by the given fact that similar modules, Reactor1 and Reactor2 share common failures such as OCAP_SPC. Each module have different occurrences of OCAP_SPC but in this network, they overlap. It is also observed from the proof of concept that for given symptoms, all modules have 33.33% probability of occurrence that confirms the added confusion.

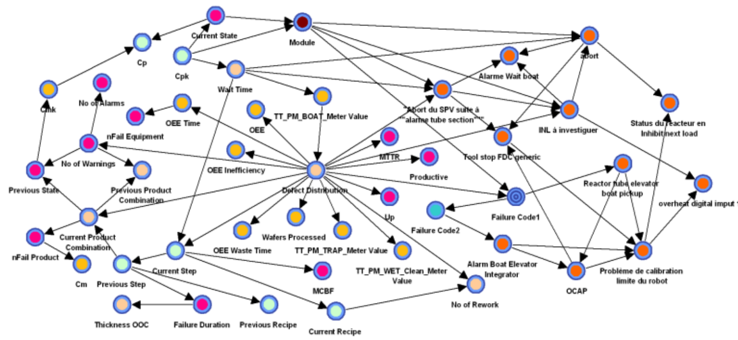



Figure 16 - Failure-Cause diagnosis BBN model at equipment level

Some of the prediction accuracy results for the equipment level BBN model are presented in Figures 17 with gain and ROC curves. The results clearly show the declined gain and increasing false positive that significantly reduces the diagnosis capability of the equipment level BBN model.

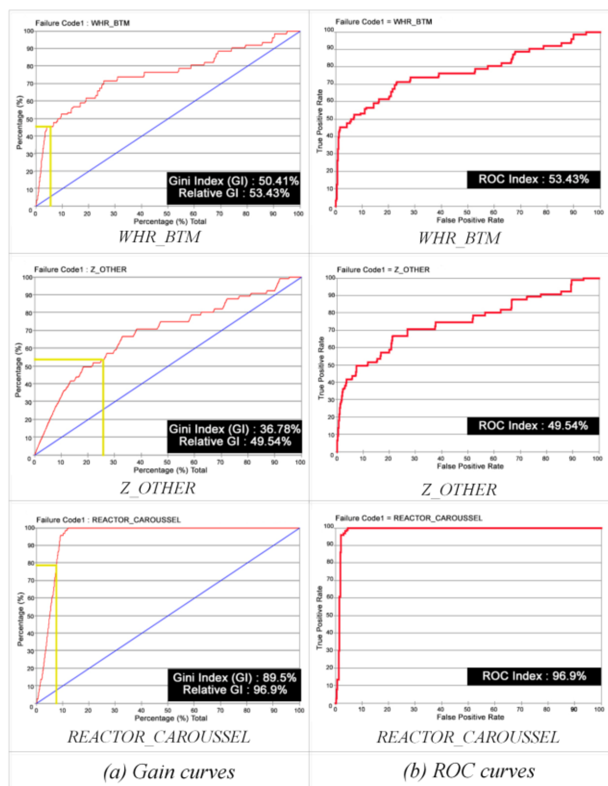



Figure 17 - Gain and ROC curves for equipment Level BBN model

### 4.4. Comparison of Diagnosis Accuracy for Equipment vs. Model Level BBN Models (Step-4)

The diagnosis accuracy from equipment and module level BBNs are presented in Figure 18. The accuracy is computed as an average of reliability and precision for each BBN model. It shows that module level BBN has almost overall 99.7% prediction accuracy in comparison to 54% for equipment level model. The gain obtained in diagnosis with module level BBNs is 45.7% that is significant and can help in reducing unscheduled equipment breakdowns. The likely reason for misdiagnosis by equipment level BBN is the commonality in failures between different modules that add confusion. Hence, it's evident to get accuracy over equipment level BBNs when failures-causes diagnosis are modeled at module levels.

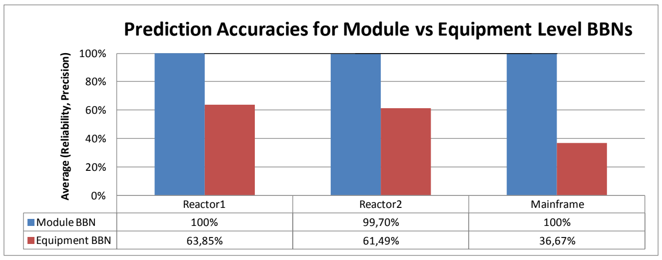



Figure 18 - Gain in prediction accuracy for module level BBNs over equipment level

## 5. DISCUSSION AND PERSPECTIVES

Above results advocate the hypothesis that misdiagnosis is the reasons for increased unscheduled breakdowns. It is due to the fact that existing failure diagnosis approaches model equipment as a single unit and use FDC sensor data. These approaches also make an assumption that product quality drifts are due to equipment failures, but in actual practice, the causes can equally be traced to maintenance, product or process. In the SI, equipment are composed of multiple modules that share symptoms, failures and causes. Besides this fact, the variability of sensor data could easily trigger a misdiagnosis and result in unstable model.

In the proposed methodology, we first modeled the failure modes against product drifts as a function of symptoms. It is the first step towards reducing unscheduled breakdowns. Then failure and cause diagnosis is modeled at module level. An equipment level BBN model is also learned in the same way and is found to be less accurate in comparison with the module level BBNs. It provides clear evidence that failure-cause diagnosis must be modeled at module level and produces more accurate results when used with data other than FDC in high-mix low-volume production lines.

The BBN models, developed in this paper as a proof of concept, are static in nature; however, real advantage lies in transforming these models into dynamic BBNs. The developed BBN models can also be used with FDC sensors data as complimentary indicators when faced with a situation where BBN model for FM identification give equal probability to all failure modes (product, process, equipment and maintenance). Therefore, it is possible to extend this work in future. The cost of maintaining these models for a complete workshop and ultimately a production line could be very high. Therefore, we believe that generalization of these models can be made for similar type of equipment with common failure behaviors.

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### REFERENCES

Ballhaus, W., Pagella, A., & Vogel, C. (2009). A change of pace for the semiconductor industry. *Technical report, German Technology, Media and Telecommunications*, Nov. 2009.

Blue, J., Roussy, A., Thieullen, A., & Pinaton, J. (2012). Efficient FDC based on hierarchical tool condition monitoring scheme. *23rd Annual SEMI Advanced Semiconductor Manufacturing Conference (ASMC)* (pp. 359-364), May 2012.

Bouaziz, M. F., Zamaï, E., & Duvivier, F. (2013). Towards Bayesian network methodology for predicting the equipment health factor of complex semiconductor systems. *International Journal of Production Research (IJPR)*, 51(15), 4597-4617.

Chang, H. J., Song, D. S., Kim, P. J., & Choi, J. Y. (2012). Spatiotemporal pattern modeling for fault detection and classification in semiconductor manufacturing. *IEEE Transactions on Semiconductor Manufacturing*, 25(1), 72-82.

Chen, A., & Blue J. (2009). Recipe-independent indicator for tool health diagnosis and predictive maintenance. *IEEE Transactions on Semiconductor Manufacturing,* 22(4), 522-535.

Chickering, D.M. (2002). Learning equivalence classes of Bayesian-network structures. *The Journal of Machine Learning Research*, 2, 445-498.

Demirli, K., & Vijayakumar, S. (2010). Fuzzy logic based assignable cause diagnosis using control chart patterns. *Information Sciences*, 180(17), 3258-3272.

Doty, L. A. (1996). *Statistical process control (2nd ed.)*. NY, USA: Industrial Press.

Glover, F. (1986). Future paths for integer programming and links to artificial intelligence. *Computers and Operations Research*, 13(5), 533-549.

He, Q.P., & Wang J. (2007). Fault detection using the k-nearest neighbor rule for semiconductor manufacturing processes. *IEEE Transactions on Semiconductor Manufacturing,* 20(4), 345 ± 354.

Isham, M.U. (2013). *Real time safety verification in the process industry using fault semantic networks (FSN)*. Doctoral dissertation. Institute of technology, University of Ontario.

Ishikawa, K., & Loftus, J. H. (1990). *Introduction to quality control (Vol. 98)*. Tokyo: 3A Corporation.

Kjærulff, U.B., & Madsen A.L. (2006). Probabilistic Networks for Practitioners – A Guide to Construction and Analysis of

Bayesian Networks and Influence Diagrams, Department of Computer Science, Aalborg University, HUGIN Expert A/S.

Kumar, R. (2008). *Fabless semiconductor implementation*. New York: McGraw-Hill.

Lacaille, J.,& Zagrebnov, M. (2007). An unsupervised diagnosis for process tool fault detection: The flexible golden pattern. *IEEE Transactions on Semiconductor Manufacturing,* 20(4), 355–363.

Lam, W., & Bacchus, F. (1994). Learning Bayesian belief networks: An approach based on the MDL principle. *Computational intelligence*, 10(3), 269-293.

Margaritis, D. (2003). *Learning Bayesian network model structure from data.*Doctoral dissertation. University of Pittsburgh.

Munteanu, P., & Bendou, M. (2001). The EQ framework for learning equivalence classes of Bayesian networks. *Proceeding IEEE International Conference on Data Mining (ICDM),* (417-424).

Pearl, J. (1988). *Probabilistic reasoning in intelligent systems: networks of plausible inference*. Morgan Kaufmann.

Roeder, G., Schellenberger, M., Schoepka, U., Pfeffer, M., Winzer ,S., Jank, S., & Pfitzner L. (2011). Approaches for Implementation of Virtual Metrology and Predictive Maintenance into Existing Fab Systems. Retrieved from http://convegni.unicatt.it/miproco/meetings_Roeder2011_06_13_Statistical_Workshop_Milan_final.pdf on 3rd January 2014.

Rooney, J. J., & Heuvel, L. N. V. (2004). Root cause analysis for beginners.*Quality progress*, 37(7), 45-56.

Sarkar, P. (2004). Clustering of event sequences for failure root cause analysis. *Quality engineering*, 16(3), 451-q460.

Selen, L. J. M., Timmermans, E. A. H., & Bolscher, G. (2009). *U.S. Patent No. 7553516 B2*. Washington, DC: U.S. Patent and Trademark Office. Retrieved from http://www.google.fr/ patents/US7553516 on 21st March 2014

Shahzad, M. K., Hubac, S., Siadat, A., & Tollenaere, M. (2011). An Extended Business Model to Ensure Time-to-Quality in Semiconductor Manufacturing Industry. *International Conference on Enterprise Information Systems*, Portugal.

Smith, G. M. (2004). *Statistical process control and quality improvement (5th ed.)*. NJ, USA: Pearson/Prentice Hall.

Susto, G., Pampuri, S., Schirru, A., & Beghi, A. (2012). Optimal tuning of epitaxy pyrometers. *Proceeding of 23rd IEEE/SEMI Advanced Semiconductor Manufacturing Conference (ASMC)*, (294–299).

Teyssier, M. & Koller, D. (2005). Ordering-based search: A simple and effective algorithm for learning Bayesian networks. *Conference in Uncertainty of Artificial Intelligence (UAI)*.

Verron, S., Li, J., & Tiplica, T. (2010). Fault detection and isolation of faults in a multivariate process with Bayesian network, *Journal of Process Control*, 20(8), 902-911.

Weber, P., and Jouffe, L., (2006), Complex system reliability modeling with Dynamic Object Oriented Bayesian Networks (DOOBN). *Reliability Engineering and system Safety,* 91, 149-162.

Weidl, G., Madsen, A. L., & Israelson, S. (2005). Applications of object-oriented Bayesian networks for condition monitoring, root cause analysis and decision support on operation of complex continuous processes. *Computers & chemical engineering*, 29(9), 1996-2009.

Yang, L., & Lee, J. (2012). Bayesian Belief Network-based approach for diagnostics and prognostics of semiconductor manufacturing. *Robotics and Computer-Integrated Manufacturing,* 28, 66-74.

Yoon, M., & Malerba, F. (2010). Technological interrelatedness, knowledge generality and economies of scale in the evolution of firm boundaries: A history-friendly model of the fabless ecosystem. *International Conference on Opening Up Innovation: Strategy, Organization and Technology*.

Yue, H.H. & Tomoyasu, M. (2004). Weighted PCA and its applications to improve FDC performance. *Proceeding 43rd IEEE Conference on Decision and Control,* (4262–4267).

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